EMOTION DETECTION IN CUSTOMER SERVICE: A CNN-BASED APPROACH TO EMPLOYEE ENGAGEMENT

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Annotatsiya: Ushbu maqolada konvolyutsion neyron tarmoqlari (CNN) yordamida xodimlarning mijozlar bilan muloqoti davomida ularning hissiyotlarini aniqlash, shuningdek, deep learning texnologiyasini marketing va inson resurslarini boshqarishda qo‘llash masalalari o‘rganiladi. Tadqiqotda hissiy tahlil xodimlarning samaradorligi va mijozlar qoniqishiga qanday ta’sir ko‘rsatishi ta’kidlanadi. Ma'lumotlar yig‘ilib, oldindan qayta ishlangan va CNN modelini o‘rgatish uchun ishlatilgan, ammo ma’lumotlar to‘plamining cheklangan hajmi tufayli past aniqlik kabi qiyinchiliklar aniqlangan. Tadqiqotda model samaradorligini oshirish uchun individual o‘qitish yondashuvlarini taklif qiladi. Natijalar chuqur o‘rganishni biznes jarayonlariga integratsiya qilish mijozlarga yo‘naltirilgan strategiyalarni va xodimlarni rag‘batlantirish tizimlarini yaxshilashi mumkinligini ko‘rsatadi.

Kalit so‘zlar: Deep learning, CNN, hissiyotlarni aniqlash, xodimlar samaradorligi, mijozlar bilan muloqot.

Abstract: This paper explores the use of Convolutional Neural Networks (CNNs) in detecting employee emotions during customer interactions, focusing on the application of deep learning in marketing and human resource management. The research emphasizes how emotional analysis can provide insights into employee performance and customer satisfaction. Data was collected, preprocessed, and used to train a CNN model, though challenges such as low accuracy due to limited dataset size were identified. The study proposes solutions to improve model performance, including individualized training approaches. The findings suggest that integrating deep learning into business processes could enhance customer-centric strategies and employee incentive systems.

Key words: Deep learning, CNN, Emotion Detection, Employee performance, Customer interaction.

Аннотация: В данной работе исследуется использование сверточных нейронных сетей (CNN) для обнаружения эмоций сотрудников во время взаимодействия с клиентами, с акцентом на применение глубокого обучения в маркетинге и управлении персоналом. Исследование подчеркивает, как эмоциональный анализ может дать представление о производительности сотрудников и удовлетворенности клиентов. Были собраны, предварительно обработаны данные и использованы для обучения модели CNN, хотя были выявлены такие проблемы, как низкая точность из-за ограниченного объема данных. В исследовании предложены решения для улучшения производительности модели, включая индивидуализированные подходы к обучению. Результаты показывают, что интеграция глубокого обучения в бизнес-процессы может улучшить стратегии, ориентированные на клиентов, и системы стимулирования сотрудников.

Ключевые слова: Deep learning, CNN, обнаружение эмоций, производительность сотрудников, взаимодействие с клиентами.

INTRODUCTION

Deep learning, a subset of machine learning, has seen remarkable growth in recent years, transforming industries and business practices. This rapid development is driven by advances in computational power and the availability of large datasets, enabling deep learning models such as Convolutional Neural Networks (CNNs) to excel in complex tasks like image recognition, natural language processing, and emotion detection. CNNs, in particular, stand out due to their ability to learn hierarchical representation from data, making them ideal for capturing intricate patterns in both structured and unstructured information.

The business world has begun to recognize the value of deep learning, particularly in enhancing customer service and employee performance. In customer-facing industries, maintaining positive interactions is crucial for business success. Understanding the emotional state of employees during these interactions can offer valuable insights into customer satisfaction and employee engagement.

In this paper, we propose leveraging CNNs to detect employee emotions in real-time as they communicate with customers. The goal is to analyze the proportion of time employees exhibit positive emotions, such as happiness and satisfaction, versus negative emotions, such as frustration or anger. By implementing such a system, businesses can encourage positive behavior through incentives like performance-based bonuses or salary adjustments, ultimately fostering a more customer-centric environment. This approach offers a novel way to blend deep learning with human resources management, optimizing employee performance and improving customer experience simultaneously.

Neural Network

2.1 **Single Neuron – Perceptron** A perceptron, the fundamental unit of artificial neural networks, processing inputs through a weighted sum and an activation function: $f_{1NN}(x;W,b)=\sigma(W\cdot x+b)$

where is the weight vector, is the bias, and represents activation functions like Sigmoid, Hyperbolic Tangent, and ReLU. These functions enable non-linear modeling but require iterative weight optimization via gradient descent: $w \leftarrow w-\eta\frac{\partial L}{\partial w}$

While effective for linear data, perceptrons struggle with non-linear patterns, prompting the use of multilayer networks.

2.2 Deep Neural Networks Deep neural networks (DNNs) consist of multiple layers, enhancing the modeling of complex non-linear functions. They can be represented as:

$$f_{DNN}(x)=f_{1NN}\big(f_{1NN}(\cdots f_{1NN}(x)\cdots)\big)\ (k\ layers),$$

comprising input, output, and hidden layers.

2.3 Weight Optimization Weight optimization aims to minimize the loss function:

$$w^{*}=\arg\min_{w\in W} L(f_{DNN}(x;w),y).$$

While simple perceptrons allow for convex optimization, deep neural networks face significant challenges due to the vast number of parameters involved. A common strategy is to employ gradient-based methods, where the parameters are adjusted based on the gradients of the loss L with respect to the weights. The backpropagation algorithm enhances efficiency by calculating gradients layer by layer, leveraging previously computed values via the chain rule.

2.4 **Regularization** To prevent overfitting, regularization techniques are crucial, including:

(1) **Weight Decay**: Adds a penalty for large weights.
(2) **Dropout**: Randomly deactivates neurons during training.
(3) **Batch Normalization**: Normalizes layer outputs for faster training.

These methods collectively improve model generalization and robustness.

2.5 **Convolutional Neural Networks** Convolutional Neural Networks (CNNs) are specialized for processing grid-like data, such as images, by exploiting spatial dependencies among neighboring pixels. The architecture consists of multiple layers that capture features at various levels: lower layers identify simple patterns (e.g., edges), while higher layers combine these patterns to form complex representations.

The key operation in CNNs is convolution, where a filter or kernel is applied to the input data to extract relevant features. This is mathematically defined as:

$$f_{CNN}(x)_{ij}=\sum_{x=-\frac{l}{2}}^{\frac{l}{2}}\sum_{y=-\frac{l}{2}}^{\frac{l}{2}} x_{i+x,j+y}\,k_{xy},$$

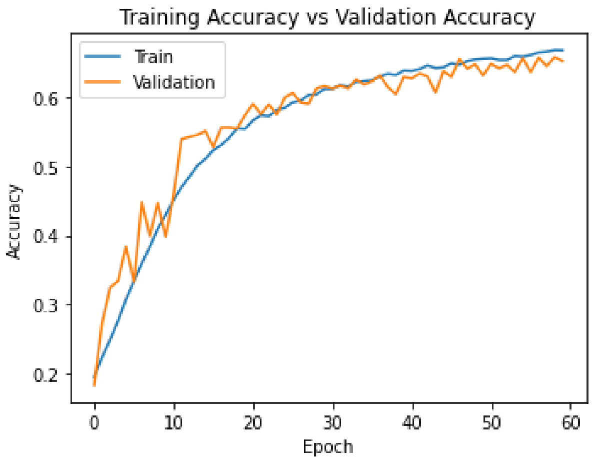
with zero-padding to maintain valid boundaries. The extracted features are then fed into fully connected layers for classification. This capability makes CNNs particularly effective for tasks such as emotion detection during employee-customer interactions.

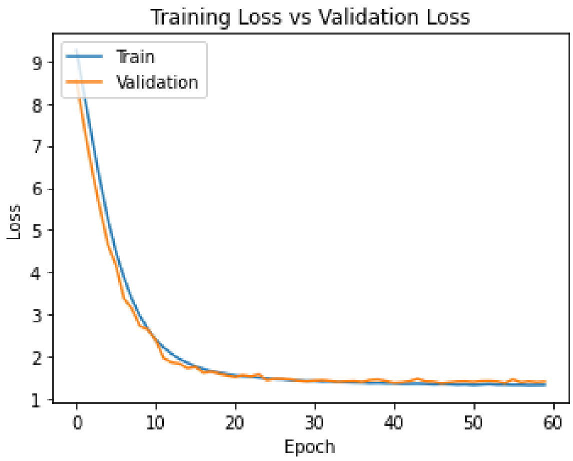
Model Development and Data Collection

3.1 **Convolutional Neural Network Architecture** To develop our model, we utilized TensorFlow, which provides an accessible interface through the Keras API. This framework simplifies the process of building and training deep learning models. For our application, we employed a Sequential model, allowing us to stack layers in a linear fashion, making it suitable for our Convolutional Neural Network (CNN) architecture.

3.2 **Data Collection and Preprocessing** Data collection is a critical step in training our model. We gathered images from various online sources, categorizing them into distinct folders based on emotional expressions such as “positive_emotions”, “negative_emotions” and “neutral”. This organization facilitates the training process by ensuring that each class is adequately represented.

Following data collection, we performed several preprocessing steps to prepare the images for training. These steps included resizing the images to a uniform dimension, normalizing pixel values, and augmenting the dataset to enhance the model’s robustness against overfitting. In total, we compiled a dataset of 7,688 images for training and 849 images for testing. The performance of our model was evaluated, with results summarized in the following figures, illustrating the accuracy and loss function throughout the training process.





3.3 **Challenges and Strategies for Improving Accuracy** The low training accuracy observed in our model can be attributed to several factors. Firstly, the limited size of the dataset may not adequately represent the diversity of emotional expressions and variations among individuals. While we collected a total of 7,688 training images, this number may still be insufficient for the model to generalize effectively across different scenarios and employee characteristics. Additionally, variability in image quality, lighting conditions, and backgrounds could further contribute to the model's inability to learn robust features.

To improve accuracy, it would be beneficial to train the model for each individual employee. This approach can enhance the model's ability to recognize subtle emotional expressions. By setting up the camera to capture images from a consistent angle and background for each employee, we can ensure that the model learns to extract features specific to their expressions, thereby improving recognition accuracy.

SUMMARY

This study investigates the use of Convolutional Neural Networks (CNNs) to detect employee emotions during customer interactions, aiming to enhance both employee performance and customer satisfaction. We developed a CNN model using TensorFlow and the Keras API, supported by a diverse dataset categorized by emotional states.

While the model demonstrated functional capabilities, challenges in accuracy were noted, primarily due to limited data representation and variability in image quality. To address these issues, we proposed targeted training for individual employees to improve recognition of subtle emotional expressions.

The findings highlight the potential of deep learning to transform marketing and human resource management by enabling businesses to foster a more customer-centric environment and develop effective incentive programs based on emotional engagement.

References

1. Mathias K, Stefan F, Asil O. Deep learning in business analytics and operations research: Models, applications and managerial implications.
2. I Goodfellow, Yoshua B, Aaron C. Deep learning
3. Schmidhuber, J. (2015). Deep learning in neural networks: An overview. Neural networks
4. Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2017). Reshaping business with artificial intelligence: Closing the gap between ambition and action.
5. Kratzwald, B., Ilić, S., Kraus, M., Feuerriegel, S., & Prendinger, H. (2018). Deep learning for affective computing: Text-based emotion recognition in decision support. Decision Support Systems